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**Final Report on
Exploratory Study on
Intelligent Multi-Radar Multi-Target Tracking
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ABSTRACT

This report describes a target association methodology known as Constellation Matching (CM) and its application to multiple target tracking. The method, together with others, has been integrated into a Multiple Target Tracking (MTT) system. The MTT system implemented consists of four components: 1) data preprocessing, 2) gating, 3) data association, and 4) filtering and prediction.

The CM method is different from the traditional data association methods such as NNSF, MHT and JPDA in the sense that it makes full use of the target spatial configuration information for the plot-to-target assignment. To speed up the CM process, two heuristics are incorporated: 1) the use of spatial constraints to eliminate impossible assignments and 2) the use of maximum entropy partitioning method to subdivide the graph representation into subgraphs with lower order to increase the matching speed and reduce the computation complexity.

The CM method is then combined with Kalman Filter techniques for target tracking as well as further data association. The efficiency and accuracy of one depends on those of the other. To demonstrate and evaluate the capability of the CM-based MTT system developed, real world radar data provided by DREO are used. The experimental results show that the CM-based MTT system is effective in accomplishing its task in most cases even in noisy environment.

For comparison purpose, an MTT system based on Multiple Hypothesis Testing (MHT) is also implemented in this report. The results on the same data set are obtained using both the MHT-based MTT system and the CM-based MTT system. The comparison show that in most cases, CM-based MTT system yields better results. Other advantages and disadvantages of both methods are also analyzed and reported.

1 Introduction

Multiple target tracking (MTT) is an essential requirement for surveillance systems employing one or more radars to interpret target activity within the range of the radar stations. The objective of MTT is to construct the locations of multiple moving targets in consecutive time frames from a sequence of data obtained by the same radar station(s).

From the detected target positions in each time frame, a tracking system first makes association of the positions of the same target in different time frames and then updates the estimated trajectory (or track). Hence, the two major parts of the tracking process are: a) complete the association of targets in consecutive time frames and b) use the updated trajectory to predict and later confirm each target position in succeeding frames.

For single target tracking, a sequence of target positions can be detected from sensed data which is referred to as plots. They can be plotted to give a trajectory of the target. And, the detected trajectory up to the current frame can be used to predict the position of the target in the next frame based on the associated statistical information. However, for a multiple target tracking situation (say n targets), one of the difficult problems is to make correct association of the same target between consecutive frames. Even if one tries all the n^2 combinations, it is still difficult to compute the correct (or the best) association. This problem is further aggravated by the presence of noise which may look like targets.

Although standard Kalman filter techniques can be applied to estimate the track of a target, its application is only feasible if the trajectories prior to the time of prediction exist and the motion of the target can be assumed to be linear during the interval between successive time frames. However, in the beginning of the track, in general, there is no obvious way for associating targets with the same identity. Techniques such as **nearest neighbor rule** and **multiple hypothesis method** may help, yet often there are situations where their robustness is questionable. Furthermore, most targets do not undertake regular behavior all the time, sometimes they will make a sharp turn, therefore, the filtering process cannot get correct result.

Recently artificial neural networks have also been considered for multiple target tracking. However, Such technologies work well only when the occurrence of events would follow certain probabilistic rules which have to be learned from a significantly large amount of data. Its ef-

fectiveness diminishes if the event occurrence deviates significantly from the regular behavior of the previous patterns or when the decision parameters become large.

Methods based on fuzzy logic controller has also been proposed for a target tracking system. Systems such as that reported in [21] are able to track a single non-maneuvering target. The performance of the controller is optimized primarily for error and then for computation time. Small improvements in error reduction can be made by changing the membership functions but the major improvement is in rule base learning. As with the neural network approach, the rule base has to be learned. In many real world situations, this requirement is not possible. Method using a fuzzy logic controller for multiple target tracking has not been reported.

In this report, a methodology developed in the PAMI Lab has been adopted to provide a solution to this problem. It uses a method known as constellation matching [6] to establish the multiple target association in the early frames and later to combine its efficacy with Kalman filter to track and confirm the trajectories of multiple targets. It exploits, in the most direct way, the spatial configuration of the collection of targets which are subject to probabilistic temporal and spatial constraints. Thus, it renders redundancy, in the "global" configuration of the targets to counter (or minimize) possible errors arisen from local target positional variation or false alarms due to the presence of noise. By using a hierarchical maximum entropy partitioning method, it is able to partition the data points into subdomains of low problem size so as to constrain the space and computational complexity. This method can therefore be applied to data with a large number of targets and noise

2 Problem Statement

The multiple target tracking (MTT) system employed in our experiment is a track-while-scan (TWS) system in which the data are received at regular intervals as the radar regularly scans a predetermined search volume. There are mainly two kinds of source for such measurements in each scan: targets of interest (we call *true targets*) and background noise sources such as radar ground clutter, or internal error sources (we call *false targets*). The basic tracking is to estimate the position and/or other properties of the target, using the available sequential plots. For multi-target tracking, the problem of associating the plots with targets has to be solved.

3 Approaches

The complete MTT system is shown in Figure 1. Below is a detailed explanation.

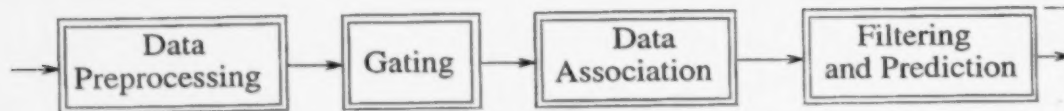


Figure 1: Multiple Target Tracking System

Each component in this figure will be discussed in the following sections.

3.1 Data Preprocessing

The measured kinematic quantities of data points may not be in the suitable form for performing MTT functions. Hence, the first step for an MTT system is **data preprocessing** which transforms the original data into an acceptable format for subsequent analysis. For convenience of constellation matching, the original data is transformed from a polar system to a Cartesian coordinate system by:

$$x = range * \cos(azimuth)$$

$$y = range * \sin(azimuth)$$

3.2 Gating

The second step for an MTT system is **gating** which is used to partition the observed data points in the next frame into two categories: 1) candidates (to be considered for subsequent data association or track update) within the connected neighborhoods (or gates) of points in the previous frame; and b) data points that can be considered for new tentative track initiation. Figure 2 illustrates the application of gating to four new observations based on the gates of two points in the previous frame.

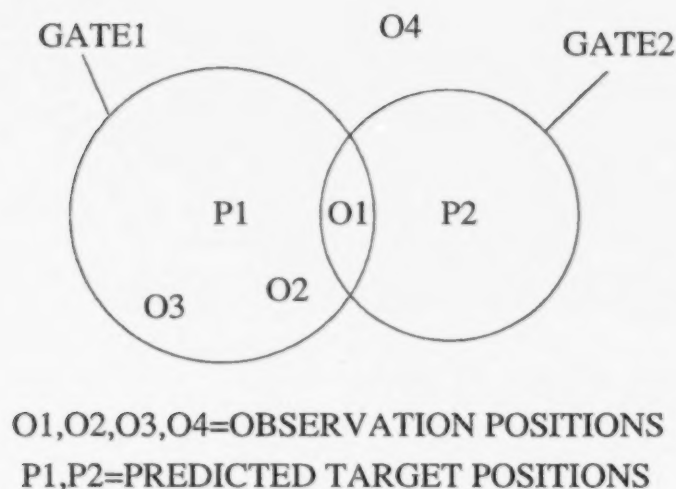


Figure 2: Gating and Correlation for Two Closely Spaced Tracks

In this figure, $P1$ and $P2$ are two points in the previous frame. Let $O1, O2, O3$ and $O4$ be four observations in the current frame. GATE1 and GATE2 are the neighborhoods of $P1$ and $P2$ respectively with the maximum estimated target displacement between consecutive time frames as their respective radius. Here, $O1, O2$ and $O3$ fall within GATE1 whereas $O1$ falls also within GATE2. Hence, $O1, O2$ and $O3$ can all be considered to be associated with $P1$ whereas $O1$ can be considered as associated with either $P1$ or $P2$. These belong to the first category. $O4$ is outside both gates and hence cannot be associated with either $P1$ and $P2$, hence, $O4$ belongs to the second category.

In this example, one should notice that more than one observation, i.e. $O1, O2$ and $O3$ fall into the same gate (GATE1) and thus can be associated with $P1$ in the previous frame. Furthermore, an observation such as $O1$ in the current frame could be associated with more than one targets, i.e. $P1$ and $P2$. Often, an observation may not lie inside a gate of any existing track (or point). In such cases, the observation becomes a candidate for the initiation of a new track, as in the case of $O4$.

3.3 Data Association

The most important and difficult task of an MTT system is *target association*. It takes the output of gating as the input and makes the final observation-to-track (or observation-to-plot) assignments. As mentioned earlier, for closely spaced targets, it is likely that conflicting situations may arise in the following cases:

1. when multiple observations fall within the same gate;
2. observations fall within the gate of more than one track (or plots).

There are several approaches to solve the target association problem in an MTT system.

Nearest-Neighbor Standard Filter (NNSF)

NNSF is an appealing approach because it decomposes the MTT problem into a set of single target tracking problems. The idea of NNSF is to estimate each object's position at the time of a new frame is received, and then assign the reports to the nearest such estimates. The optimal solution is obtained by assigning observations to tracks in order to minimize the total summed distance from all observations to the tracks to which they are assigned. Comparing with other existing methods, the computational cost of NNSF is the least. Nevertheless, once an incorrect association is made, the error usually may be carried on in the subsequent process because this method does not make use of spatial configurations of the prior plots to rectify the errors.

Joint Probabilistic Data Association (JPDA)

JPDA assigns all observations in the vicinity of a given target to that target while weighting the observations according to the frequency of counts within the target proximity. The disadvantage of this method is that it cannot effectively solve the track initiation problem. Furthermore, when the number of noise points are relatively large, the frequency counts may not be too meaningful.

Multiple Hypothesis Testing Method (MHT)

This method attempts to maintain the hypotheses of candidates and use the history of the plots for hypothesis evaluation and selection. As a result, the highly unlikely choices are eliminated and only the best choice remain. MHT is the most accurate method among the current methods. However, in some situations, if there are too many

observed points in a frame, the MHT tree would become so large that its feasibility cannot be guaranteed. Furthermore, MHT depends heavily on the correctness of prediction. Sometimes, when a target is making an abrupt change of course, it would be very difficult to make a correct prediction. In such cases, the accuracy would be degraded drastically.

Constellation Matching Data Association Method (CM)

The CM method adopted for data association is a special case of a much more general methodology known as optimal attributed subgraph isomorphism [6,8-12], the principles of which will be described in the next section. With this method, the optimal target matching is achieved by assigning observations to tracks (or possible target points in the previous frame) in order to minimize a certain objective function.

In CM, the objective function takes into the consideration of preservation of spatial configuration of associated points between consecutive frames (or among a sequence of consecutive frames), in principle, it guarantees global optimization. In both NNSF and JPDA, the objective functions are the sum of localized deviation between associated points in consecutive frames. Hence the optimization is quite local.

CM is similar to MHT in that they both generate possible data correspondence between two consecutive frames during data association. While CM chooses the best solution based on a "global" optimization, MHT generates a number of candidate hypotheses and uses new data to select the best one.

Among the result of gating and target association, some observations obtained may not be assigned to any existing track such as *O4* in Figure 2. In this case some new tentative tracks are generated. In Figure 2, *O4* can be considered as the initial point of a new track. However, because of the presence of noise, a confirmation is usually required to determine whether or not the observation is really the track of a true target. In our algorithm, if no confirming observations are received in the next three consecutive scans, the previous observations are considered as false targets and thus dismissed. If a track is not updated any further, it should be deleted.

3.4 Filtering and Prediction

The final step for MTT system is **filtering and prediction** which incorporate the correlated observations into the updated estimates of the track positions. This procedure is necessary and important because of the following:

First, if no current observation can be associated with a track, then a prediction based on the proceeding points of the trajectory would serve as an assumed observation for the current frame.

Second, the prediction is used to define the center of the gated region for gating.

Here the traditional Kalman filtering is used for filtering and prediction. The details will be given in the next section.

4 Methodology

As mentioned earlier, the most important part of an MTT system is its target association strategy. The research carried out in this project is focused heavily on this aspect coupling with the target predicting and filtering. In this research project, we have developed a system capable of achieving these two tasks using **Constellation Matching Method** and **Kalman Filter Method**. The efficiency and accuracy of each phase relies on that of the other. The result of data association is used to refine and update the trajectory prediction while the prediction, in the mean time, provides the probabilistic target position in the target configuration which, as whole, provides probabilistic constraints to improve the effectiveness of the association method.

4.1 Constellation Matching Method for Target Association

The association of current observation with the previous target (if the consecutive scans are adequately close in time) can be achieved through optimal constellation matching using a generic optimal graph morphism algorithm [6-12]. As explained in the previous sections, unlike the other existing methods, the target association of CM attempts to preserve maximal spatial correspondence between configurations of data points in two consecutive frames. The general principles of CM is briefly described here:

A group of N targets $\{T_i, i = 1, \dots, N\}$ is represented by an attributed graph G in which each target T_i is represented by a vertex v_i and $d(T_i, T_j)$, the distance between T_i and T_j , is the attribute value assigned to the edge (v_i, v_j) . The attributed graph G so defined is referred to as a **constellation**.

Let $G1$ and $G2$ be the constellations in two consecutive frames respectively. Association between targets in different frames can be realized by establishing an **optimal one-to-one mapping** f between the vertices in $G1$ and $G2$ while optimizing a certain objective function F . F is defined as:

$$F(G1, G2) = \sum_{\forall V_i, V_j \in G1, i \neq j} C(V_i, V_j)$$

where

$$C(V_i, V_j) = \begin{cases} 0 & \text{if any one of } V_i, V_j, f(V_i), f(V_j) \text{ is null} \\ |d(V_i, V_j) - d(f(V_i), f(V_j))| & \text{otherwise} \end{cases}$$

Note that the objective function F is contributed by the difference of distance between all data pairs in both constellations.

Choose f that achieves optimal target matching which minimizes F . We denote such optimal mapping by f^* .

The pseudocode of the **algorithm** used in our experiment is given below.

step 1: for each pair v_i and v_j in $G1$, compute $d(v_i, v_j)$;

step 2: for each pair u_i and u_j in $G2$, compute $d(u_i, u_j)$;

step 3: find each possible mapping, i.e. find in $G2$ a set of points $u_1', u_2', \dots, u_{N1}'$ where u_i' can be a null vertex (one that assumes a null value but can still be matched to a v_i in $G1$) or an actual vertex in $G2$ so that u_i' is matched to v_i in $G1$;

step 4: for each feasible mapping, compute the value of the **objective function** F ;

step 5: choose the mapping f^* that **minimizes** F .

Though this method is theoretically sound for target association, some minor problems have to be resolved to make the implementation feasible. The problems are described as follow:-

1. When the number of vertices in a graph is too large (say larger than 10), the solution tree will become so large that this method becomes infeasible.
2. The accuracy of this method would be affected by noise in the background. If the noise level is too high, the correctness of the target matching would be degraded.

To solve the first problem by speeding up the matching process, the solution tree is pruned using the following heuristics which take advantage of the temporal and spatial constraints:

A basic assumption of the MTT system is that the distance a target can reach within a time interval between consecutive frames cannot exceed a predefined maximum value. Thus, a prespecified maximum size of the predicted region is imposed while finding the possible matches between vertices in $G1$ and $G2$ [6-12]. This spatial constraint is used at the beginning of tracking when filtering and prediction cannot be used because there are not enough plots to render meaningful prediction.

Another assumption is that the distortion of a constellation cannot exceed a certain value, i.e. $C(V_i, V_j)$ cannot exceed a predefined maximum value. Hence, a prespecified tolerance of the change in distance between two consecutive frames is introduced in our CM system to eliminate those infeasible matches.

When more and more plots are received, filtering and prediction operations can then be applied to predict the next position of a particular target so as to reduce the search space in the constellation matching process.

In the case where too many vertices in $G1$ need to be matched to vertices in $G2$, a space partitioning method using the maximum entropy method [14,15] can be introduced to partition $G1$ into several subgraphs (or sub-constellations), each of which would contain

say 5-10 vertices. Thus the solution space for constellation matching is drastically reduced. This makes the CM method for scenarios with large number of plots feasible and effective.

In order to avoid the effect of noise, some filtering preprocessing should be conducted before using the MTT system for gating.

4.2 Initial Target Tracking and Trajectory Generation

The maximum size of the predicted region is used as the prespecified spatial constraint for the optimal match at the start of the algorithm.

There are two kinds of observations in a frame:

1. isolated observations and
2. closely spaced observations.

Isolated Observation

An isolated observation is one which is far from other observations in the same time frame. In other words its predicted region does not overlap with that of the others. Once a new frame is received, three cases may arise depending on the number of observations in its predicted region:

If there is **no observation** in its predicted region, the region is enlarged to the prespecified size. If there is still none, then no assignment can be made to that isolated observation.

If **only one observation** is found in its predicted region, then it is assigned to the proceeding isolated observation.

If **more than one observation** is found in its predicted region, then use the prediction to choose the most suitable observation for the assignment.

Closely spaced observations

Closely spaced observations are those whose predicted regions overlap with others. We group those observations to form a cluster. For example, P_1, P_2, P_3, P_4 and P_5 in

Figure 3 induce a connected overlapping predicted region that form a cluster. These five points constitutes $G1$.

In the new frame, choose those observations that lie within the combined region (or cluster) to form another constellation $G2$. Then apply constellation matching to find the target association between $G1$ and $G2$.

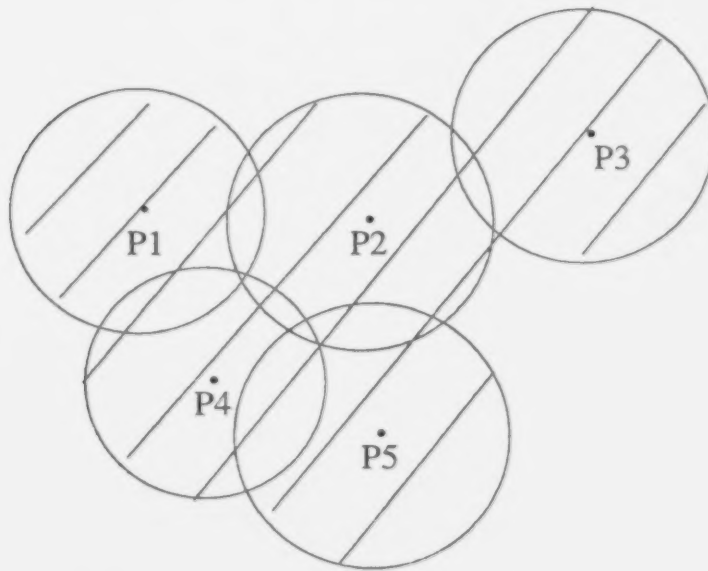


Figure 3: Combination of Predicted Regions of Closely Spaced Points

4.3 Multiple Target Trajectory Prediction and Updating

Here Kalman filtering is applied for trajectory prediction and updating. When the trajectories in the previous frames assume a regular behavior, they can be used to predict new target positions.

In our MTT, a Kalman filter is used to help CM by providing spatial constraints in reducing the search space as CM is rectifying the possible incorrect predictions of the Kalman filter. This point together with trajectory updating will be elaborated in the following paragraph.

In order to further evaluate the result and update the trajectory, the predicted points obtained by the Kalman filter in the new frame can be used to induce predicted regions for gating. The predicted region will provide a broader yet constrained space to support more

effective target association. In this case, the use of CM for matching plots in consecutive frames within the connected region is able to rectify the target prediction obtained by the Kalman filter which is able to use regular and local information in prediction.

Applying Kalman filter to MTT has other advantages too. These include the followings:

The use of the Kalman filter will minimize the mean-squared error as long as the target dynamics and the measurement noise are accurately modeled.

The same filter can be used for varying targets and measurement environments by changing a few key parameters.

The Kalman gain sequence automatically adapts to the changing of the detection histories.

The Kalman filter provides a convenient measure for the estimation accuracy.

Assume that

$$\mathbf{x}(k) = \begin{pmatrix} x(k) \\ y(k) \end{pmatrix} \text{ where } (x(k), y(k)) \text{ is the } k\text{-th time point of the specific target.}$$

$$\hat{\mathbf{x}}(k+1) = \Phi \hat{\mathbf{x}}(k) + K(k)[m(k) - H \hat{\mathbf{x}}(k)]$$

$$K(k) = \Phi P(k) H^T [H P(k) H^T + R(k)]^{-1}$$

$$P(k+1) = [\Phi - K(k)H] P(k) \Phi^T + Q(k)$$

The state estimation of each track is obtained recursively using these equations. As a result each track is updated and the position of the new point corresponding to each track is predicted before receiving a new data set.

5 Implementation

There are mainly five steps in our MTT system:

Step 1: Data Preproccession

The coordinate system transformation equation is the same as that described in Section

3. The output of this step is suitable for other processes afterwards.

Step 2: Gating and Clustering

The purpose of this step is to classify an observation in the last frame into one of the two categories: *isolated observation* and *closely spaced observation*. In the latter case, clustering is used to form constellations for the future target association.

Step 3: Data Association

Constellation matching method is used to obtain the correspondence between the observations in the last frame and those in the new frame.

Step 4: Track Formation

Put each assigned observation into its corresponding track which records the trajectory of the associated target.

Step 5: Trajectory Prediction

If there are more than five observations in a track, a Kalman filter is applied to obtain the predicted targets' position in the next frame. Then, the constellation matching method is applied to match these predictions to the new observations instead of matching the previous observations to the new observations.

6 Experiment Results of CM based MTT

The database applied in our experiment contains raw radar data on the formations of closely spaced military aircrafts. It is well suited for computer simulation of target tracking techniques in a multi-target environment. The data base which is provided by DREO contains primary and secondary radar returns not only from the closely spaced targets which undergo similar maneuver but also from many well separated targets which undergo a variety of maneuvers.

Four types of data are included in the database. They are: primary radar detection (ASR), secondary radar detection (SSR), correlated detections from primary and secondary radars (SSRC) and time marks (TIME).

The data base contains four files: R1T1.DAT, R1T2.DAT, R2T1.DAT and R2T2.DAT. Table 1 provides the statistics of the experimental results when our MMT is applied to these four sets of data.

In this figure, each column shows the results for each data file. The tabulated data are described as below:-

1. The first row tabulates the total number of constellation matchings conducted between consecutive frames.
2. The second row reports the number of constellation matchings that yield correct data association out of the total number tabulated in the first row.
3. The third row reports the number of constellation matchings which do not yield completely correct data association due to abrupt change of the trajectory.
4. The fourth row reports the number of constellation matchings which do not yield completely correct data association due to the presence of noise.
5. The fifth row reports the number of constellation matchings which do not yield completely correct data association due to the missing information in the plots.

	R1T1	R1T2	R2T1	R2T2
No. of Occurance of Constellation Matching	172	177	187	168
No. of Correct Constellation Matching	145	143	147	137
No of Wrong Constellation Matching due to Sudden change	16	21	29	19
No of Wrong Constellation Matching due to Noise	8	5	3	8
No of Wrong Constellation Matching due to Info. Lose	3	8	6	4

Table 1:Result of MTT Based on CM

In order to test the correctness of our Constellation Matching Method we have conducted experiments on relatively simple cases as well as the more complicated ones:-

The best way for testing the validity of the method is to use targets with known ID as the criteria for judging whether or not a match is correct or wrong. We delete all ASR data from the original data set to form a simplified data set. In such a data set, each observation in a frame has its own ID. This makes it easy to compare the tracking result with the true trajectory. Since it is impossible to show the complete result of constellation matching frame by frame in detail (there are totally around 180 frames), we only plot part of it in Figure 4. In order to get the detailed information of the change of formation of this constellation we also plot a sequence of time-frames which include only observations contained in this constellation. Figure 5 shows the observed results.

After examining the results of the constellation matching method using the simplified data set, we put the ASR data back to the data. Also, we use the ID to check the accuracy of CM, i.e. during each step of target association, we match all the observations (both ASR and SSR) between the two consecutive frames. But for testing, we are only able to know whether or not it is a correct match for the SSR data. From ASR data we cannot obtain such information. There are usually five or six targets in a group displaying a similar behavior. But, only two of them are given ID. To test the correctness of CM, we could only use targets with known ID's for confirmation. If a target in the previous frame is associated with the target in the succeeding frame with the same ID, we consider it a correct match.

Part of the global result of one constellation matching is shown in Figure 6. Also, a sequence of time-frames are plotted in Figure 7 to illustrate the matching results. Figure 8 and Figure 9 show the global results of two typical targets in R1T1.DAT (with id as 130 and 205 respectively).

While CM plays the key role in data association, Kalman filter for trajectory prediction is introduced in our MTT system for the following reasons.

When the aircrafts are flying in a normal way, the track prediction should be close to the true position. In such a case, the accuracy of target association will be high.

When an aircraft disappears in one frame we can use this prediction as the assumed track (supposing that the true track is the same as the predicted one), and proceed to the next scan, taking this prediction as the old observation. This will solve the information loss problem when the track of one aircraft breaks up for some reasons.

The prediction can play a role of connecting the missing data with the observed data under such situation.

The disadvantage of the prediction is that quite often the aircraft may change its direction drastically to the extent that the prediction cannot reflect the real track. In this case the predictions would likely lead to a wrong match.

7 MTT based on Multiple Hypothesis (MH)

In order to compare the performance of MTT based on CM with that based on MH, an MTT algorithm using a current MH method [5,16,18-20] is implemented and applied to the same set of radar data. The objective of this comparison is to examine the advantages and disadvantages of each method.

In some complicated situations it is very difficult to get correct data association based only on information obtained from two consecutive frames. Hence, the Multiple Hypothesis Method has been introduced by a number of researchers to solve this problem. As described in Section 3, this method may not achieve the best data association right after a new data set is received. However, it is able to defer the hypothesis evaluation several frames later when all the information in these frames can be used for the final selection of the optimal solution.

7.1 The Implementation of Multiple Hypothesis based on the MTT algorithm

The main idea of Multiple Hypothesis Method is that if difficult correlation decisions arise when a new data set is received (i.e. when it is hard to decide on the target correspondence), the decision is postponed while all reasonably likely "competing target assignments" are formed and used as active hypotheses. Each hypothesis is then assigned a probability value. It is anticipated that incorrect hypotheses will lead to highly unlikely cumulative probabilities and hence only the most likely hypothesis will be found at the end.

The Multiple Hypothesis System conducted in our experiment is mainly based on the approach described in Chapter 10 and Chapter 14 of "Multiple-Target Tracking with Radar Applications" [20]. The equation used is:

$$P_r(k) = (1/c)(P_D)^{N_c}(1 - P_D)^{N_t - N_c}(B_{ft})^{N_f}(B_{kt})^{N_n} \prod_{j=1}^{N_c} N[y_k - H_k x_{e_{k|k-1}}, S] * P_r(k-1),$$

which is taken from the paper “Data Association Algorithms for Multiple Target Tracking”[16]. It is implemented in our Lab for hypothesis probability calculations. The theoretical details are provided from the book entitled: “Tracking and Data Association” [19] for more theoretical details.

The flowchart of our Multiple Hypothesis Method is given in Figure 10

7.2 Experimental Results

Though the Multiple Hypothesis Method is theoretically sound for data association it encounters some problems because of its high computation cost. In a background with dense noise points the number of observations within each frame would increase. As a consequence, the number of hypotheses would increase exponentially. In order to limit the growth of the hypothesis tree, other auxiliary methods used in our CM based MTT such as those described below have been introduced into the MH based MTT system so that we have a common base for comparison with our CM method.

1. Gating: only those observations that fall within the gate of the corresponding track are considered as valid candidates to be associated with this target.
2. Pruning: hypotheses with low probability are eliminated from the decision tree. Here, in order to reduce the number of possible hypotheses we limit the number of new tracks generated to at most three for each track obtained in the previous frame.
3. Merging: those tracks or hypotheses whose effects are similar (say with the same value within the newest frames) are merged to form a new track or hypothesis.
4. Clustering: those hypotheses which interact with each other are formed into one cluster.

Plotting the result of the MH experiment

The same data sets used in testing the performance of the CM system are applied to our Multiple Hypothesis Tracking system. Figure 11 is the result of the same two targets tested by our Constellation Matching Method. A detailed comparison of MHT results with CM results will be given in the result analysis section.

8 Result Analysis

8.1 Result Analysis of CM experiment

The constellation Matching method is suitable for data association under multi-target environment where the information loss is not too much and the level of noise is not too high. Figure 12 to Figure 15 illustrate the result of a constellation matching for 5 consecutive time frames.

Although constellation matching is powerful to solve data association problem in MTT, it takes special fine tuning to make it work for real data because in some cases the number of vertices in a constellation may become so large that it results in high computation and space complexity. To overcome such problem two methods are introduced here: trajectory prediction and hierarchical partitioning using the maximum entropy method.

The trajectory prediction method is illustrated in detail in the previous section. This method is commonly used in multiple target tracking problem because of its powerfulness and efficiency. The disadvantage of this method is that in the case where the density of targets or the level of noise is too high even with trajectory prediction the complexity is still too high for our constellation matching.

Partitioning using maximum entropy is a new method developed at the PAMI lab of Univ. of Waterloo. The basic idea of this method is to partition the data space while maximizing the information content. To achieve this goal we have to divide the graph into several subgraphs which have a similar number of vertices with others. Here we limit this number to 5-10. The result of partitioning using this method is shown in Figure 16.

From the result shown in Figure 17 and Figure 18 we can see that in most cases the track prediction is close to the true position and the accuracy of constellation matching reaches 80%.

There do exist some maneuvers of targets in the sequence of time-frames which make target association more difficult. Nevertheless, from the examples supplied by DREO, we observe that constellation matching can handle most of them unless the change of direction of the aircraft is far too drastic.

Sometimes an aircraft may disappear in one frame. In such case the prediction is used as the assumed track. If this disappearance occurs at a maneuver, the prediction can act as a linkage. Otherwise some mistakes may probably have taken place.

In some cases even prediction is not enough to guarantee the correctness of data association. An example is shown in Figure 19. In this diagram for some reason target NO.130 disappears in the new time frames. Since it locates very closely with the other targets in the previous time frame, even if we use prediction we cannot avoid the wrong match(target NO.205 is regarded as target NO.130 in the new frame).

A drastic change of direction and speed of targets is shown in Figure 20. In such a case, a wrong match will be made because the basic idea of our constellation matching is to keep the change of spatial distribution to the minimum. Hence this drastic change mostly will lead to a wrong match. For example in Figure 21, the three targets do not fly in a usual way. As a result, a wrong match(target NO.130 is taken as target NO.205; target NO.0 is taken as target NO.130; target NO.205 is taken as target NO.0) results. This case occurs most often when the group making the same maneuver suddenly undertakes a sharp turn.

8.2 Result Analysis of MHT experiment

It is shown from Figure 11 that Multiple Hypothesis Method can achieve correct data association in most cases when the target does not make any unexpected behavior. However, some wrong data correspondences will be made when targets change their flying direction drastically.

The main drawback of MHT lies in these two facts:

1. In a dense target environment its computational cost is so high that it becomes impossible to be implemented. The only solution for this problem is to prune the hypothesis tree. However, there is not a way to guarantee that this prune process can always keep the best solution instead of dismissing it. When a wrong branch is pruned, it will bring a disaster to the MHT system.
2. The multiple Hypothesis method does not take into consideration the spatial constrain information contained in a group. Hence, when several targets belonging to the same group make a sharp turn it becomes quite difficult for the MHT to evaluate and choose the most likely solution.

8.3 Comparison between CM Experiment Result with MHT Experiment Result

The same four data sets have been applied to these two MTT systems and the statistics results are listed in Table 2. In order to compare MHT experiment result with CM experiment result we make the statistics basing on same targets along same time frames. It has shown that Constellation Matching Method is a sound data association approach for a MTT system. Figure 21 shows an example of the comparison between CM experiment and MHT experiment tracking the same target (id 130).

9 Future Work

Both the Constellation Matching and Kalman Filter methods are suitable for cases where information is relatively complete. We should develop a more powerful method that can deal with the case of high information loss.

By far the constraints used in Constellation Matching are static, i.e. they can be pre-specified. In real application these parameters can be determined dynamicly after some statistical computation.

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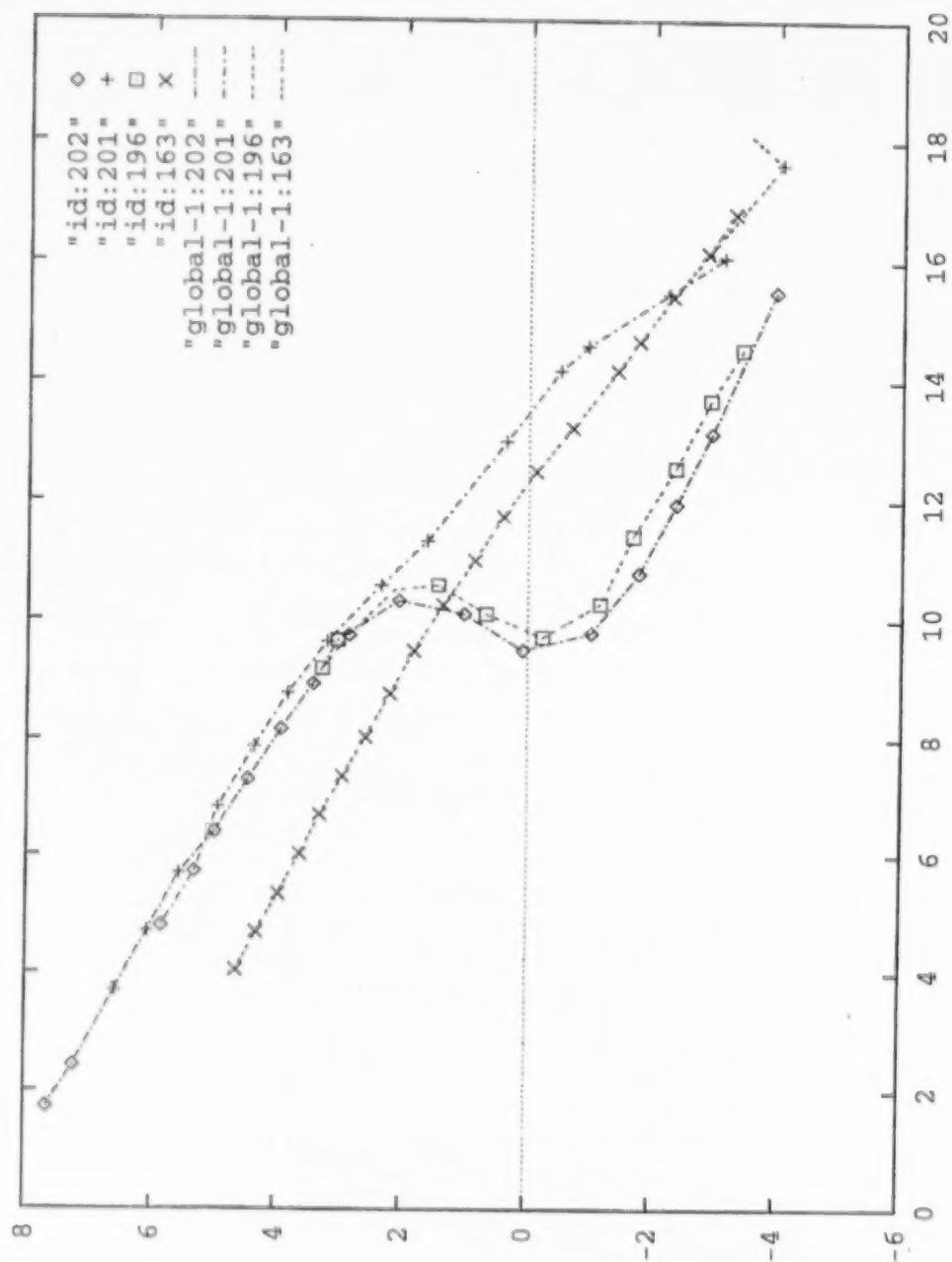


Figure 4: Part of Global Tracking Result of One Constellation(Only for SSR)

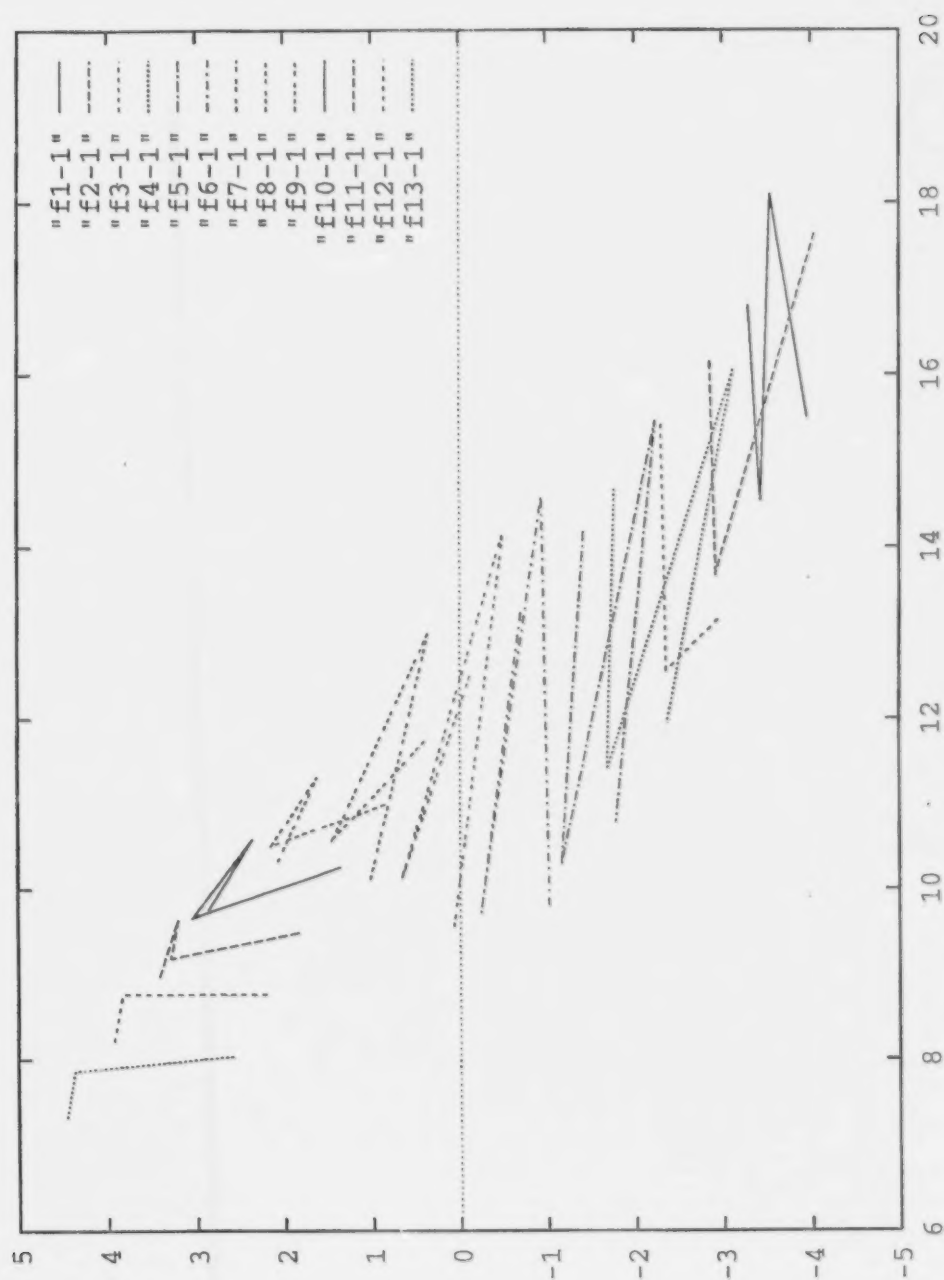


Figure 5: Part of a Sequences of Time-frames for One Constellation(Only for SSR)

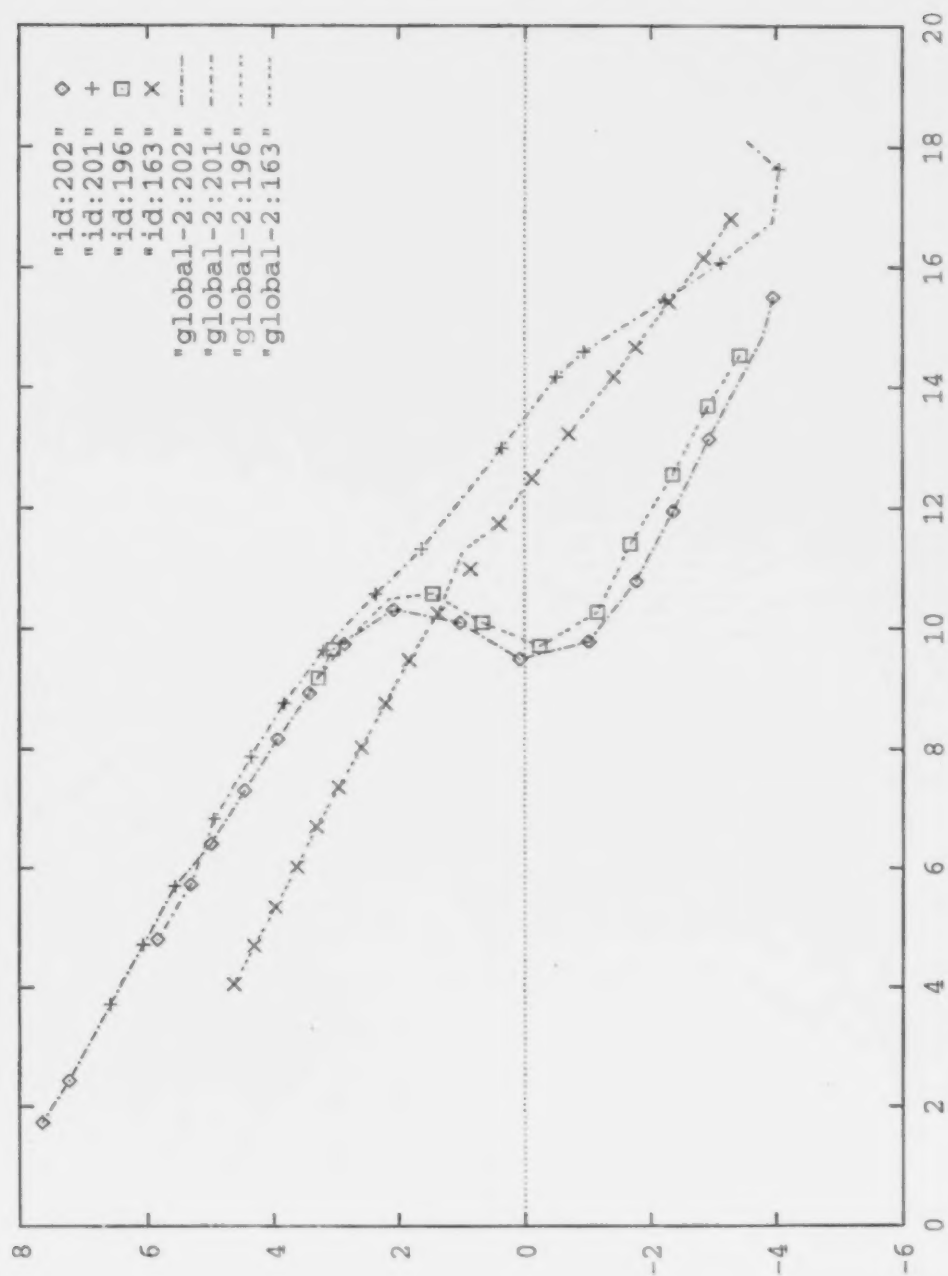


Figure 6: Part of Global Tracking Result of One Constellation(Both ASR and SSR)

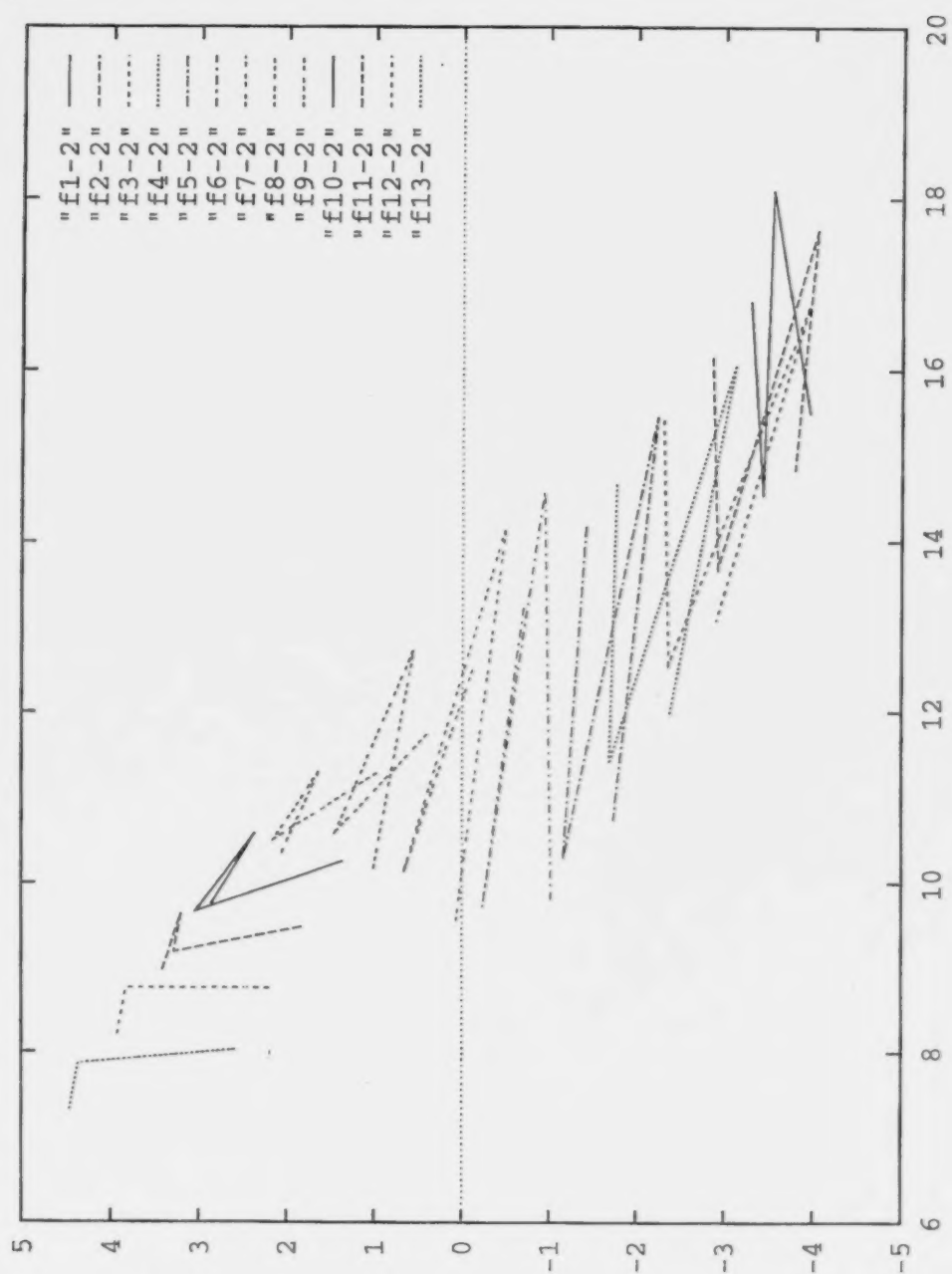


Figure 7: Part of a Sequences of Time-frames for One Constellation(Both ASR and SSR)

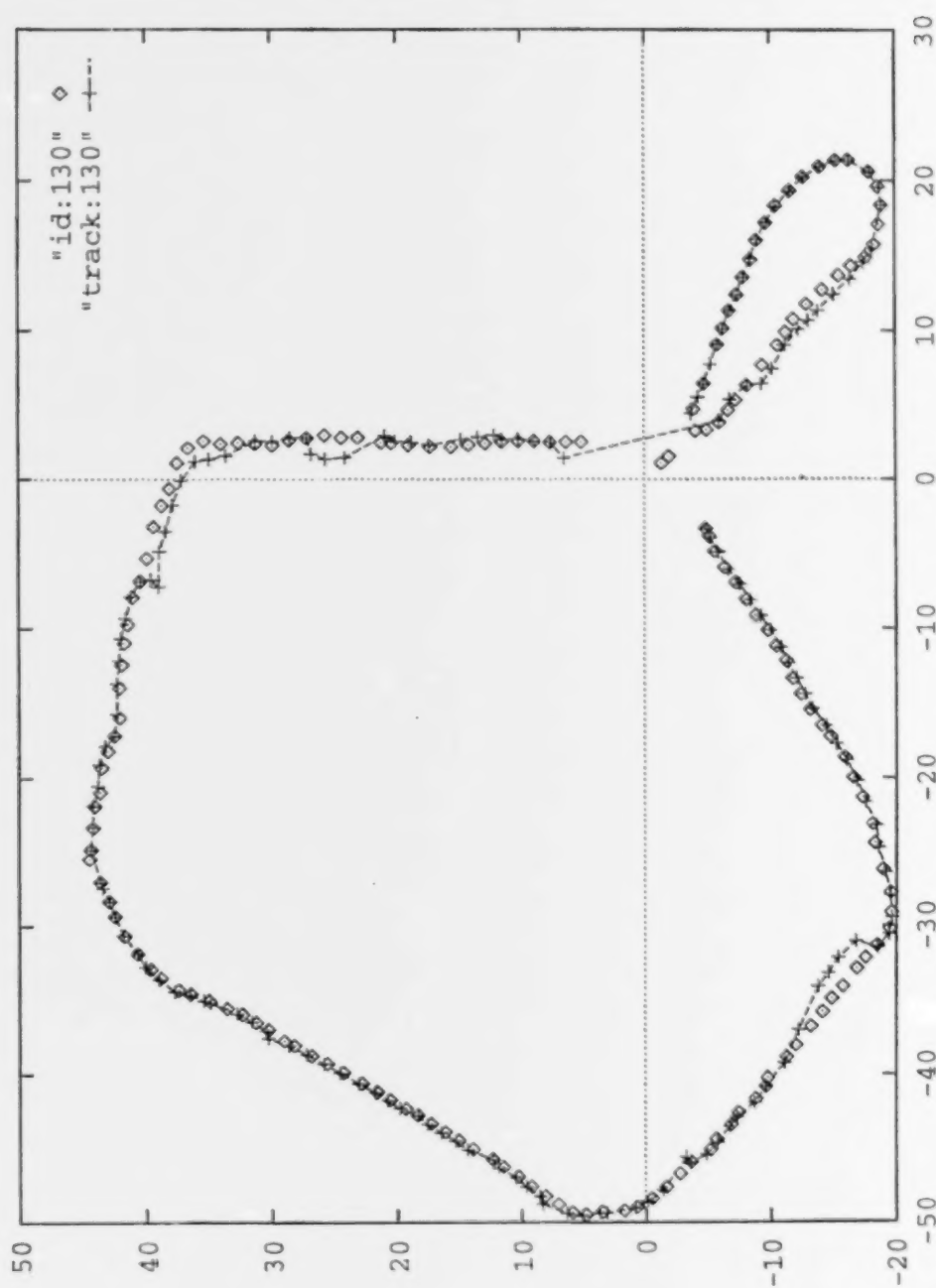


Figure 8: Global Tracking Result of One Target in R1T1.DAT(130)

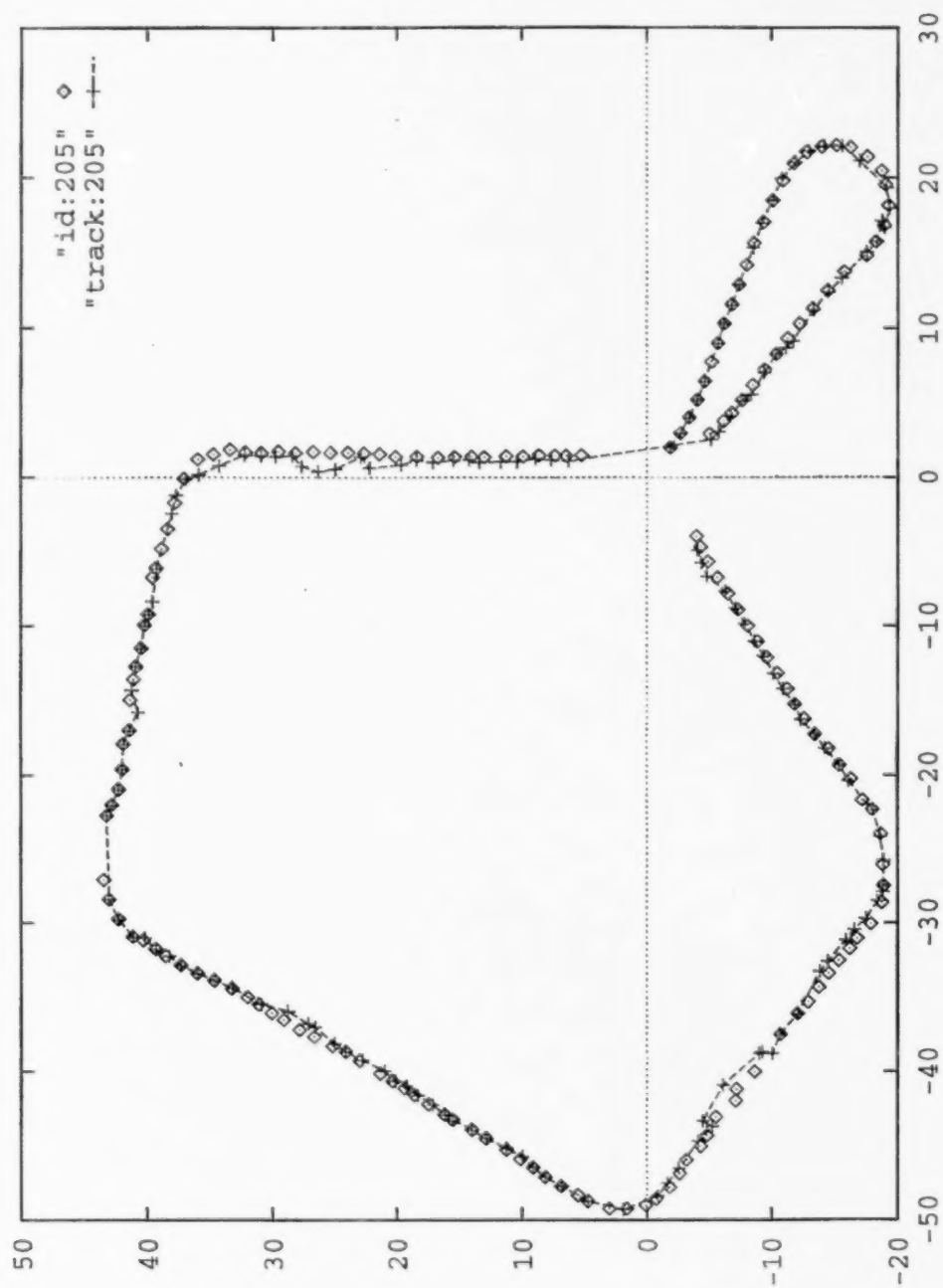


Figure 9: Global Tracking Result of One Target in R1T1.DAT(205)

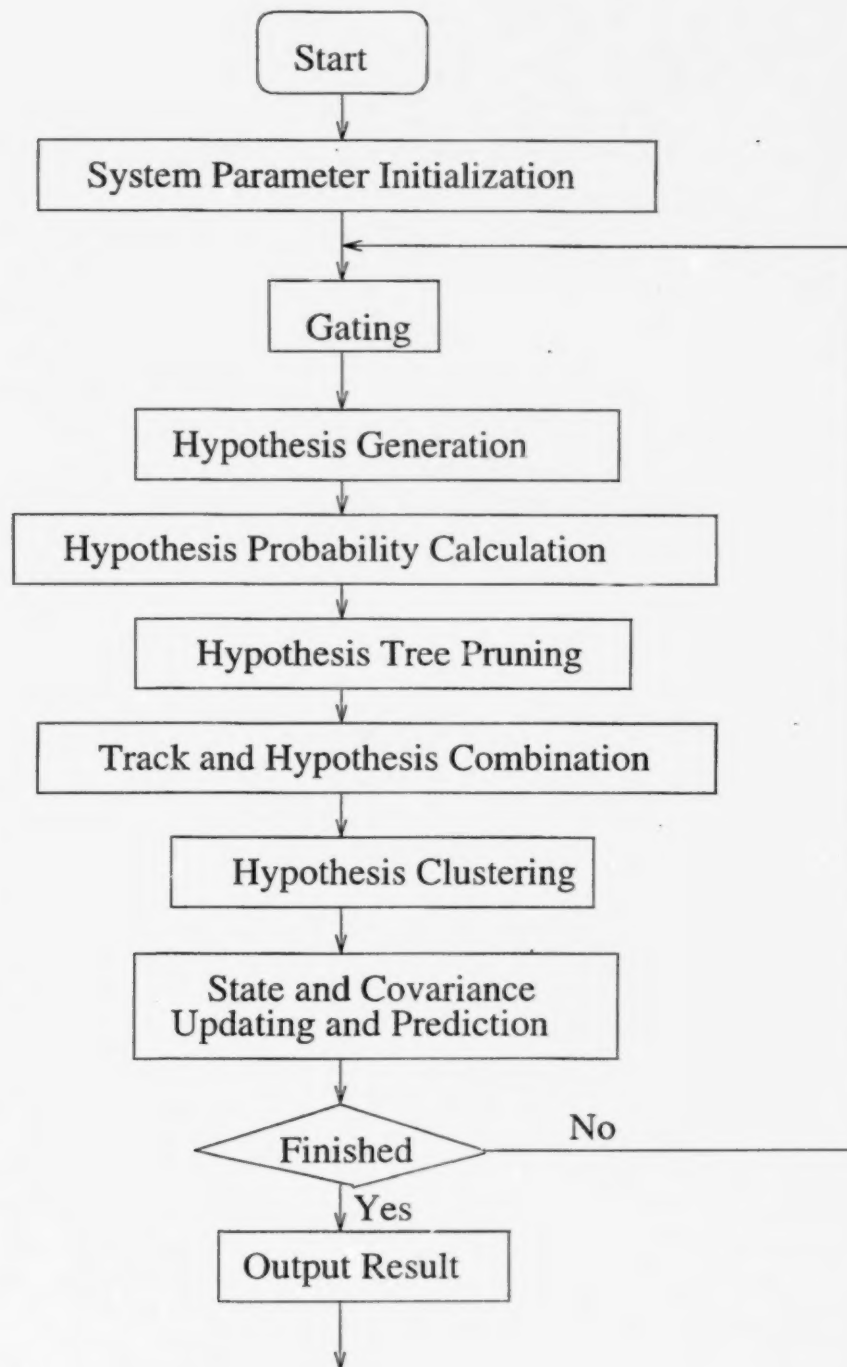


Figure 10: Multiple Hypothesis Tracking Flowchart

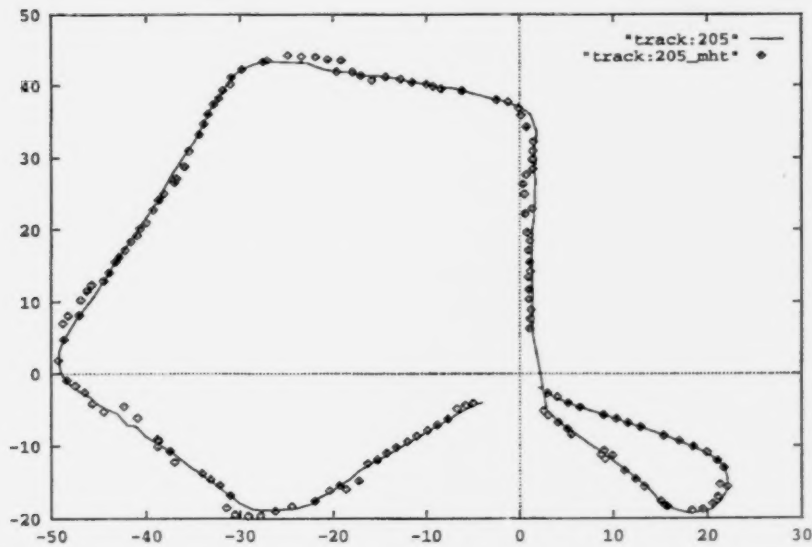
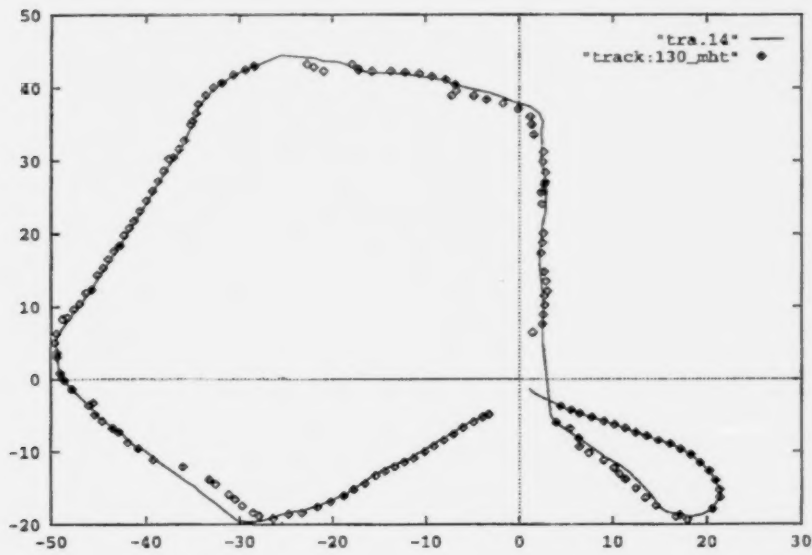


Figure 11: Multiple Hypothesis Result

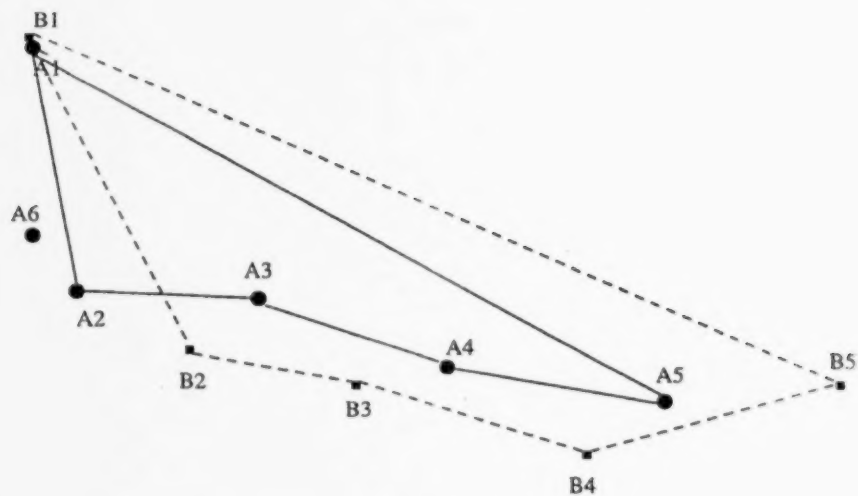


Figure 12: Pairly Constellation Matching Result1

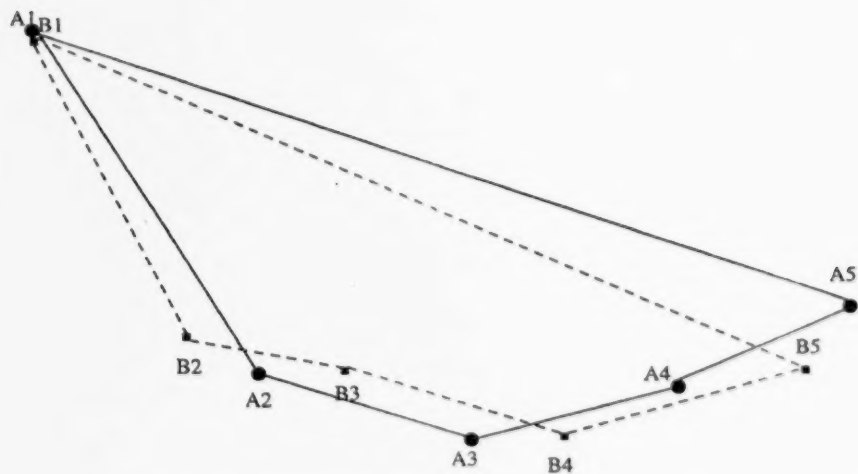


Figure 13: Pairly Constellation Matching Result2

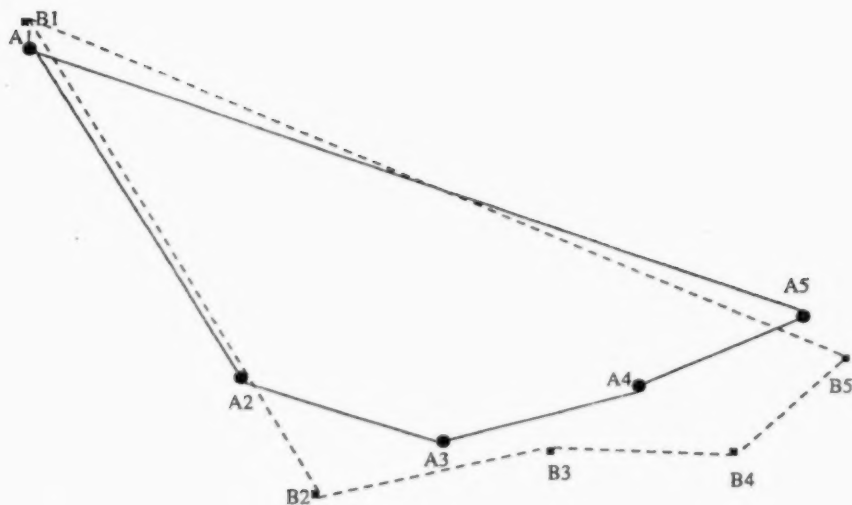


Figure 14: Pairly Constellation Matching Result3

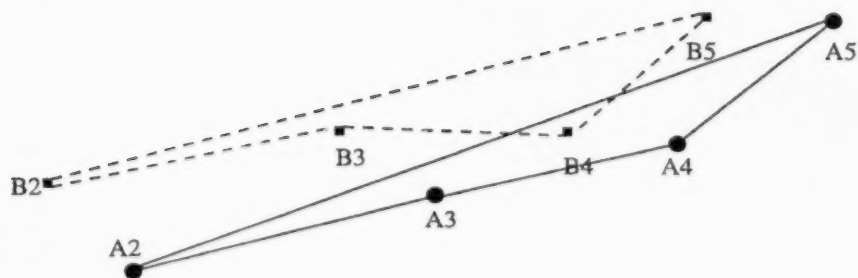


Figure 15: Pairly Constellation Matching Result4

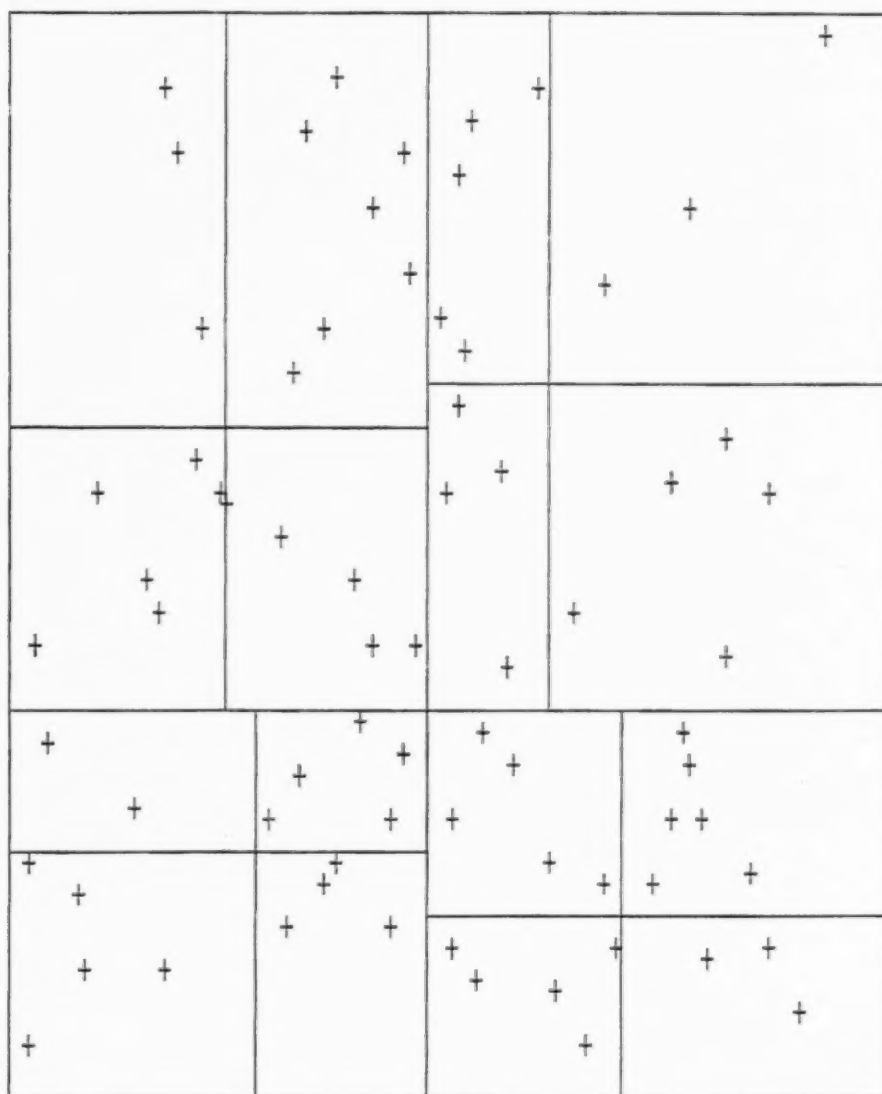


Figure 16: Result of Partitioning Using Maximum Entropy Method

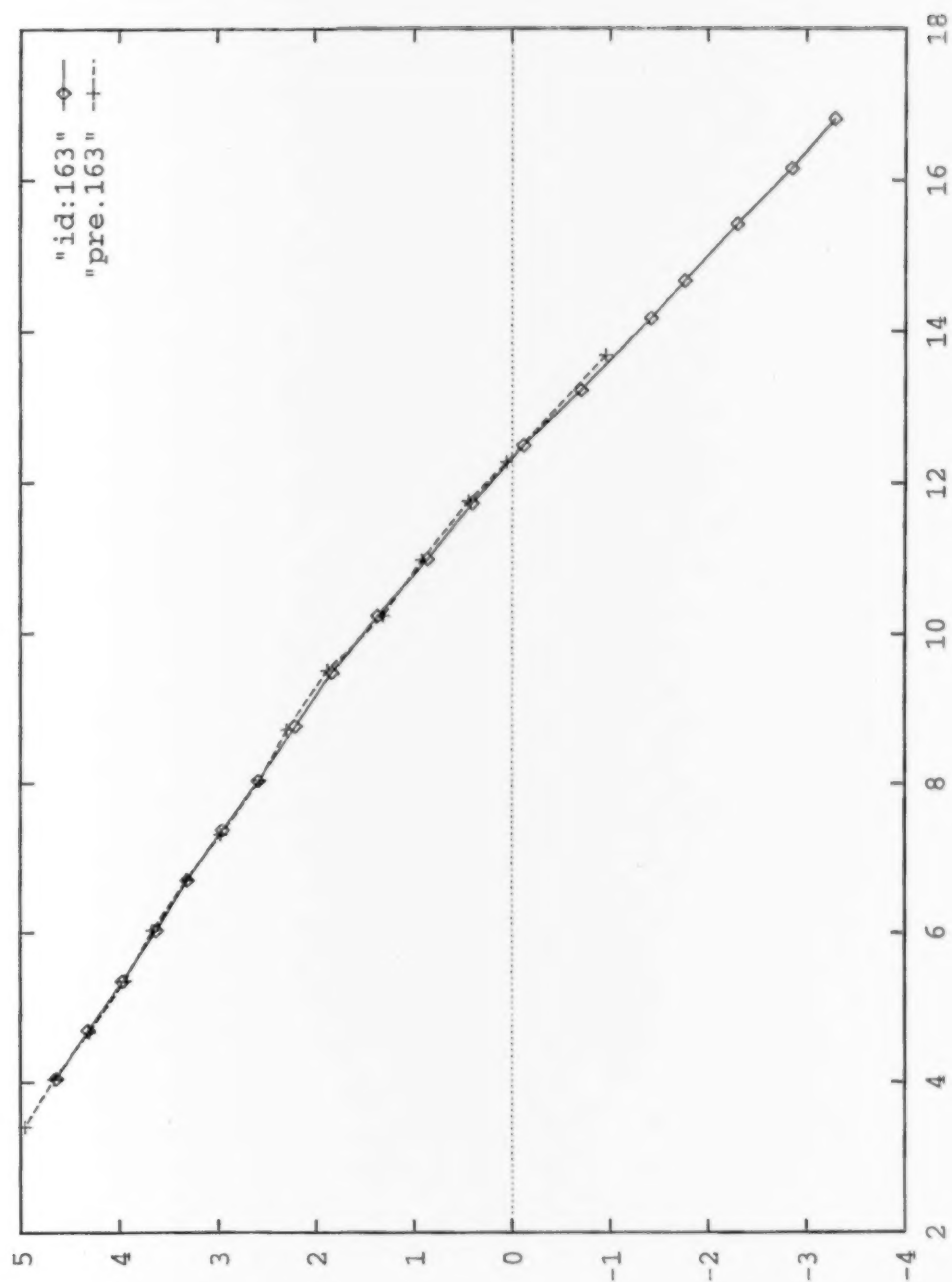


Figure 17: A Sequence of Results of Kalman Filtering for Target No.163

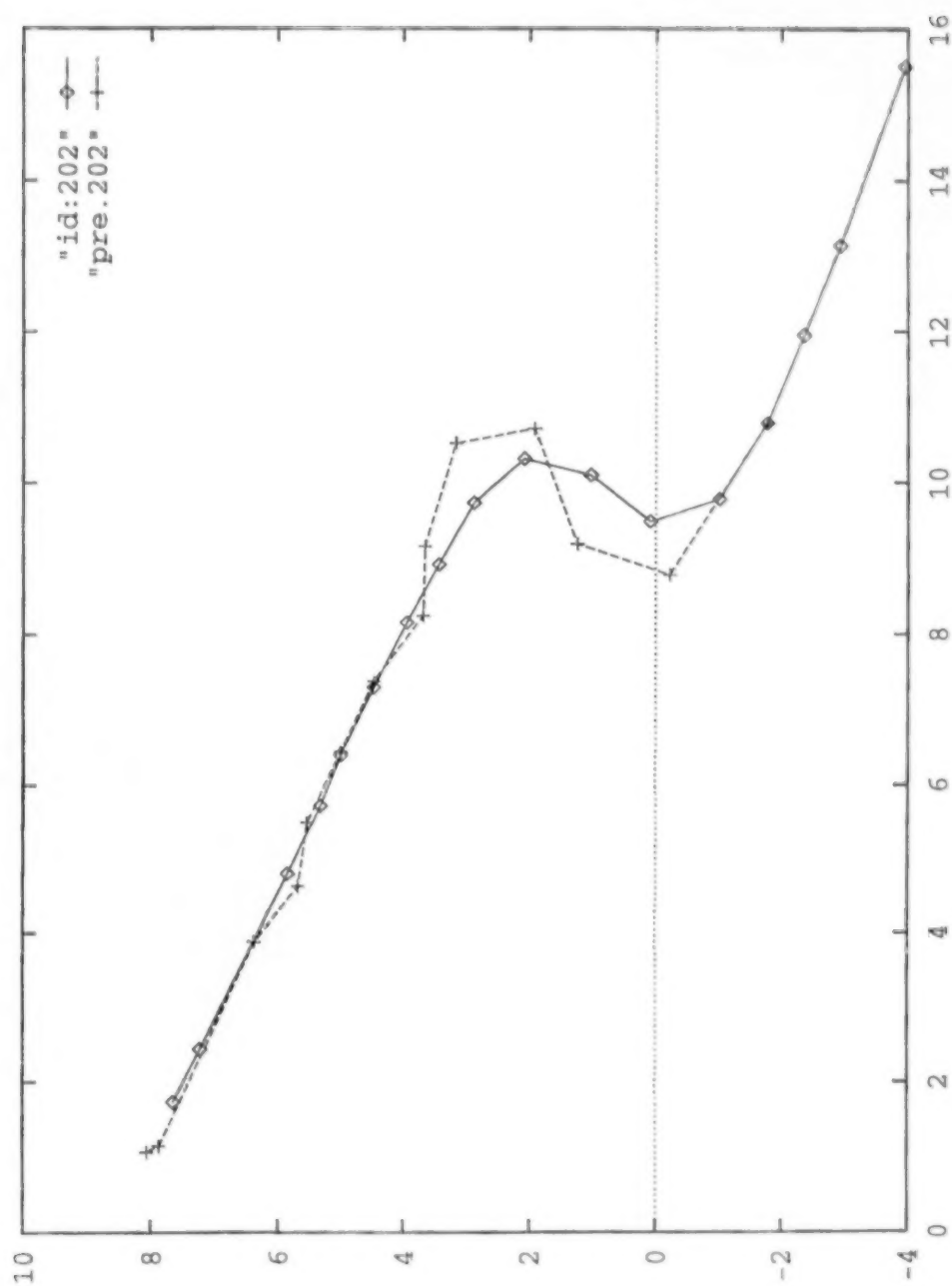


Figure 18: A Sequence of Results of Kalman Filtering for target No.202

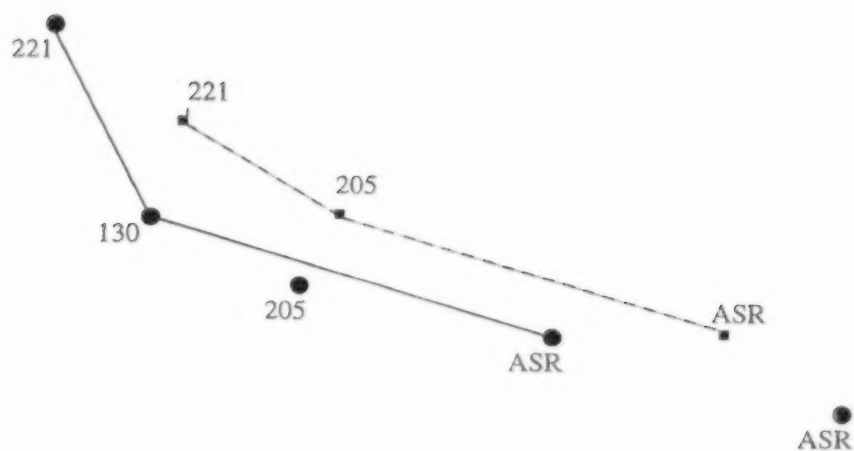


Figure 19: Wrong Constellation Matching because of Information Lose

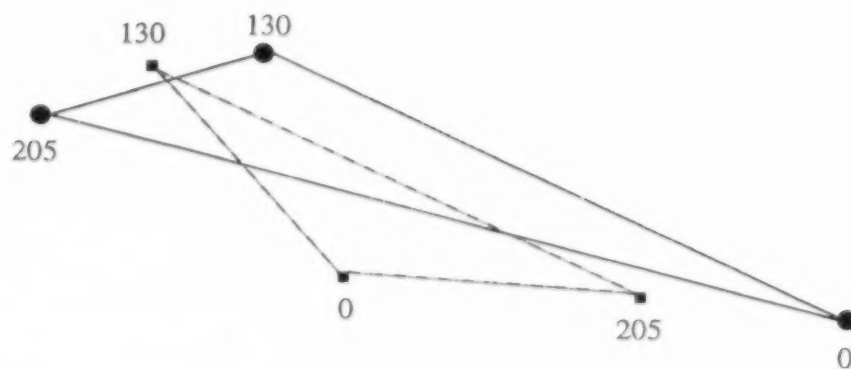


Figure 20: Wrong Constellation Matching because of Drastic Change

R1T1.DAT

	Total	Correct	Wrong
CM	172	145	27
MHT	172	130	42

R1T2.DAT

	Total	Correct	Wrong
CM	177	143	34
MHT	177	127	50

R2T1.DAT

	Total	Correct	Wrong
CM	187	147	40
MHT	187	116	71

R2T2.DAT

	Total	Correct	Wrong
CM	168	137	31
MHT	168	131	37

Figure 21: Statistics Result of CM Experiment and MHT Experiment

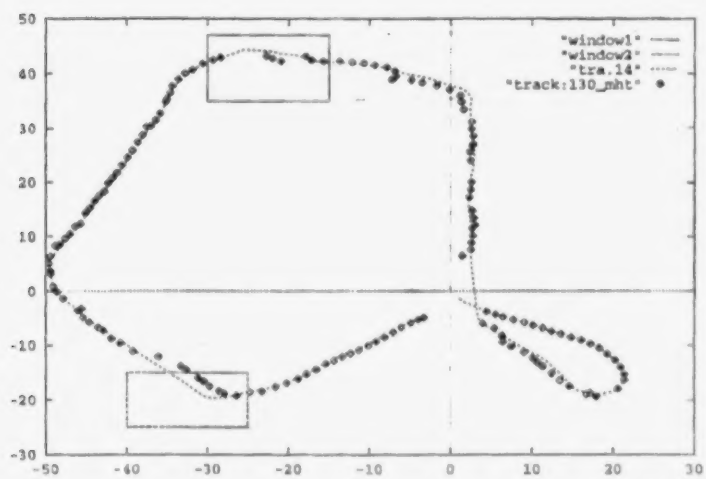
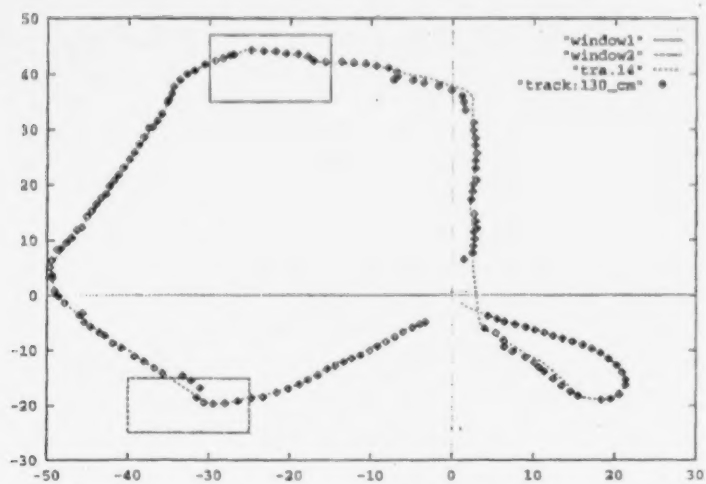


Figure 22: Comparison between CM Result and MHT Result

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This report describes a target association methodology known as Constellation Matching (CM) and its application to multiple target tracking. The CM method is different from the traditional data association methods such as NNSF, MHT and JPDA in the sense that it makes full use of the target spatial configuration information for the plot-to-target assignment. To speed up the CM process, two heuristics are incorporated: 1) the use of spatial constraints to eliminate impossible assignments and 2) the use of maximum entropy partitioning method to subdivide the graph representation into subgraphs with lower order to increase the matching speed and reduce the computation complexity.

The CM method is then combined with Kalman Filter techniques for target tracking as well as further data association. The efficiency and accuracy of one depends on those of the other. To demonstrate and evaluate the capability of the CM-based MTT system developed, real world radar data provided by DREO are used. The experimental results show that the CM-based MTT system is effective in accomplishing its task in most cases even in noisy environment.

For comparison purpose, an MTT system based on Multiple Hypothesis Testing (MHT) is also implemented in this report. The results on the same data set are obtained using both the MHT-based MTT system and the CM-based MTT system. The comparison show that in most cases, CM-based MTT system yields better results. Other advantages and disadvantages of both methods are also analyzed and reported.

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